# A FURTHER NOTE ON THE BIOMETRICAL ANALYSIS OF QUANTITATIVE INHERITANCE

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#### Introduction

In a recent paper (2) the senior author proposed a new design-called APBIB design and an alternative approach *for* the estimation of the genetic variances D and H as defined in Mather (1949) in the studies of quantitative inheritance. In this paper we shall present some numerical examples to compare the effeciency of the senior author's method with that of K. Mather (1949).

# The APBIB design and the Author's approach

In this section we give a brief account of the APBIB design and the computational procedures of the senior author's approach. As in (2) we shall confine ourselves to experiments involving the  $F_3$  lines, the  $F_2$  individuals and the parents and/or  $F_1$  individuals.

As noted in (2), the APBIB design is in essence a group-divisible PBIB design with two associates for the  $F_3$  lines and the  $F_2$  individuals, combined with a randomized complete block design for the parents and/or  $F_1$  individuals (called augmented lines). For illustration, suppose that we engage bar  $F_2$  individuals and  $ba_1$   $F_3$  lines each line with r individuals in an experiment of b blocks, each block with  $a_1+a+p$  plots and each plot with r individuals. Then in actually carrying out the experiment the first step would be to divide in a random manner the  $F_3$  lines and the  $F_2$  individuals into b groups, each group with  $a_1$   $F_3$  lines and ar  $F_2$  individuals; as a next step each group is allocated at random to one and only one of the blocks, with the  $F_3$  lines occupying  $a_1$  plots and the  $F_2$  individuals occupying a plots. The design is then completed

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by adding p augmented lines ( $P_1$  and  $P_2$  and/or  $F_1$ 's) to each block to occupy the remaining p plots and randomizing the order of the plots to make the usual hypothesis tests valid. In such a layout it is apparent that any two  $F_2$  or  $F_3$  individuals in the same block appear together in one and only one block, while any two  $F_2$  or  $F_3$  individuals in different blocks do not appear together in any block. Notice further that when an APBIB design is adopted, the following advantages can readily be observed:

- (a) It is less restrictive concerning the number of  $F_{\delta}$  lines so that the sampling error due to segregation may be reduced to some extend.
- (b) It may control the soil heterogeneity more effectively without increasing the size of the block while at the same time, the size of the plot may relatively be enlarged to control the sampling error of segregation in the  $F_3$  lines.
- (c) It renders the usual least square method as an effective procedure for estimating the genetic values of the individuals.

Adopting the APBIB design we now proceed to illustrate the principal proceedures of the senior author's approach for the estimation of the genetic variances D and H as defined by Mather (1949). Such an approach as given in this paper is based on the adoption of a fixed model without genetic and environment interaction, as was noted in (2).

(a) Let  $Y_{j(1)}$  and  $Y_{j'(2)}$  denote the jth  $F_2$  and the j'th  $F_3$  individuals respectively,  $j=1, 2...bN_{F_2}$ ;  $j'=1, 2...bN_{F_3}$ . If  $Y_{j(1)}$  and  $Y_{j'(2)}$  appear in the ith and the i'th blocks respectively, then the adjusted observations  $Q_{F_2j}$  and  $Q_{F_3j'}$  of  $Y_{j(1)}$  and  $Y_{j'(2)}$  respectively are obtained as:

$$Q_{F_2j} = Y_{j(1)} - \bar{B}_{i}$$
,  
 $Q_{F_2j'} = Y_{j'(2)} - \bar{B}_{i'}$ ,

where  $\bar{B}_{i}$  is the grand average of the *i*th block, i=1, 2...b. Similarly we obtain the adjusted value  $Q_{c_{j''}}$  of the *j''*th augmented line as

$$Q_{c_{j''}} = \sum_{i=1}^{b} \sum_{k=1}^{r} Y_{ij''k(3)} - br\bar{Y}..., j''=1, 2,...p,$$

where  $Y_{ij''k(3)}$  is the observed value of the kth individual of the j"th augmented line in the ith block and  $\bar{Y}$ ... is the grand average.

(c) Using the adjusted observations of the  $F_2$  and the  $F_3$  individuals as well as the adjusted values of the augmented lines, we obtain the estimates of the genetic values of the  $F_2$  and the  $F_3$  individuals and the augmented lines as follows: The estimate  $\hat{C}_{j''}$  of the genetic value of the j''th augmented line is obtained as  $Q_{C_{j''}}/rb$ . Denoting by  $T_{F_3i}$  and  $T_{F_2i}$  the sums of the adjusted observations of the  $F_3$  and the  $F_2$  individuals respectively in the ith block and

and

by  $T_c$  the sum of adjusted values of all augmented lines, we obtain the estimates  $\hat{f}_{2j}$  and  $\hat{f}_{3j'}$  of the genetic values of  $Y_{j(1)}$  and  $Y_{j'(2)}$  respectively as

$$\begin{split} \hat{f}_{2j} &= \mathbf{Q}_{\mathbf{F}_{2j}} + \frac{1}{rp} (\mathbf{T}_{\mathbf{F}_{2}i'} + \mathbf{T}_{\mathbf{F}_{3}i'} + \frac{1}{b} \mathbf{T}_{c}), \ j = 1, \ 2 \dots b \mathbf{N}_{\mathbf{F}_{2}} \\ \hat{f}_{3j'} &= \mathbf{Q}_{\mathbf{F}_{3j'}} + \frac{1}{rp} (\mathbf{T}_{\mathbf{F}_{2}i} + \mathbf{T}_{\mathbf{F}_{3}i} + \frac{1}{b} \mathbf{T}_{c}), \ j' = 1, \ 2 \dots b \mathbf{N}_{\mathbf{F}_{3}}, \end{split}$$

provided that  $Y_{j(1)}$  and  $Y_{j'(2)}$  appear in the *i*th and the *i'*th blocks respectively.

(c) Based on the estimates of the genetic values of the  $F_2$  and the  $F_3$  individuals as given in (b), the corresponding statistics of Mather  $V_{F_2(\sigma)}$ ,  $V_{\overline{F}_3(\sigma)}$  and  $\overline{V}_{F_3(\sigma)}$ , are obtained, with the estimate  $\hat{\sigma}^2$  of  $\sigma^2$  being given in the usual analysis of variance table (Table 2. 1).

Table 2. 1. Analysis of Variance Table

Sources of variation	d.f.	Sum of Squares	Mean Squares	Expectation
Due to adjusted values of F <sub>2</sub> , F <sub>3</sub> and parents and/or F <sub>1</sub> :	$df_1 = b(N_{F_2} + N_{F_3}) + p - 1$	$ ext{SS}_1 = \sum_{j=1}^{b  ext{N}_{\mathrm{F}_2}} \hat{f_{2j}} Q_{\mathrm{F}_{2j}} \ + \sum_{j=1}^{b  ext{N}_{\mathrm{F}_3}} \hat{f_{3j}} Q_{\mathrm{F}_3j}, \ + \sum_{j,j=1}^{p} \hat{c}_{j,j} Q_{\hat{c}_{j,j}}.$		
Blocks	$df_b = b - 1$	$SS_B = N\sum_{i=1}^{D} (\bar{B}_i - \bar{Y})^2$		
Residual	$df_e = p(rb - 1)$ $-b + 1$	$SS_e = SS_T - SS_1 - SS_B$	$SS_e/df_e = \hat{\sigma}^2$	σ²
Total	<i>b</i> N−1	$SS_{T} = \sum_{ijk} Y_{ijk}^{2} - \frac{\bar{Y}^{2} \dots}{bN}$		

where,  $N = N_{F_2} + N_{F_3} + pr$ 

(d) Finally the estimates of D, H and  $\sigma^2$  are obtained by solving the following equations:

$$\begin{cases} \frac{9}{8}D + \frac{3}{8}H + (\frac{1}{2} + K_1 + K_2)\sigma^2 = V_{F_2(e)} + V_{F_3(e)} + \frac{1}{2} | \bar{V}_{F_3(e)} \rangle \\ \frac{3}{4}D + \frac{21}{64}H + (K_1 + \frac{1}{4}K_2 + \frac{1}{2})\sigma^2 = V_{F_2(e)} + \frac{1}{4}V_{F_3(e)} + \frac{1}{2}V_{F_3(e)} \\ \frac{1}{2}(K_1 + \frac{1}{2}K_2 + \frac{1}{2})D + \frac{1}{4}(K_1 + \frac{1}{4}K_2 + \frac{1}{2})H + (K_1^2 + K_2^2 + 2)\sigma^2 \\ = K_1V_{F_2(e)} + K_2V_{F_3(e)} + \bar{V}_{F_3(e)} + \hat{\sigma}^2, \end{cases}$$

where  $K_1=1+\frac{N_{F_2}}{rp(bN_{F_2}-1)}(b-1),$   $K_2=\frac{p(a_1b-1)+a_1(b-1)}{rp(ba_1-1)}$ 

where  $N=N_{F_2}+N_{F_3}+rp$ 

## Numerical Examples

For the comparison of the senior author's approach with that of Mather (1949) as regards the estimation of the genetic variances D and H, three numerical examples were generated using the parameters given in Table (3. 1)

**Table 3. 1.** The relevant parameters for the generation of the three numerical examples

Ex. I	Ex. II	Ex. III
$\mu = 0$	$\mu$ =0	$\mu=0$
$d_a = d_b = 0.5$	$d_a=d_b=5$	$d_a = d_b = 0.5$
$h_a = h_b = 0.3$	$h_a=h_b=3$	$h_a = h_b = 0.3$
<i>e</i> ~NID(0, 9)	e~NID(0, 1)	e~NID(0, 1)
$\begin{cases} b_1=4, b_2=3, b_3=2, b_4=1 \\ b_5=-1, b_6=-2, b_7=-3, \\ b_8=-4 \end{cases}$	$\begin{cases} b_1 = 10, b_2 = 8, b_3 = 6, b_4 = 4 \\ b_5 = 2, b_6 = 0, b_7 = -2, \\ b_8 = -4 \end{cases}$	$\begin{cases} b_1 = 10, b_2 = 8, b_3 = 6, b_4 = 4 \\ b_5 = 2, b_6 = 0, b_7 = -2, \\ b_8 = -4 \end{cases}$
$N_{F_2}=32, p=4, r=16$ $N_{F_3}=64, a=2, a_1=4$	$N_{F_2}=32, p=4, r=16$ $N_{F_3}=64, a=2, a_1=4$	$N_{F_2}=32, p=4, r=16$ $N_{F_3}=64, a=2, a_1=4$
P <sub>1</sub> ; AABB= $d_a + d_b = 1.0$ P <sub>2</sub> ; $aabb = -d_a - d_b = -1.0$	P <sub>1</sub> ; AABB= $d_a + d_b = 10$ P <sub>2</sub> ; $aabb = -d_a - d_b = -10$	P <sub>1</sub> ; AABB= $d_a + d_b = 1.0$ P <sub>2</sub> ; $aabb = -d_a - d_b = -1.0$

and employing a fixed effect model, the random errors e being taken from the random normal deviates. These examples were generated according to the following rules:

(a) In generating these examples we assume a fixed effect model as given by

$$\begin{aligned} \mathbf{F}_2; \ \mathbf{Y}_{ij(1)} = \mu + b_i + f_{2j} + e_{ij(1)} \,, \\ \mathbf{F}_3; \ \mathbf{Y}_{ij'(2)} = \mu + b_i + f_{3j'} + e_{ij'(2)} \,, \\ \text{and parents}; \ \mathbf{Y}_{ij''k(3)} = \mu + b_i + c_{j''} + e_{ij''k(3)} \,, \ i = 1, \ 2 \dots b; \ j = 1, \ 2 \dots b \mathbf{N}_{\mathbf{F}_2}; \\ j' = 1, \ 2 \dots b \mathbf{N}_{\mathbf{F}_3}; \ j'' = 1, \ 2 \dots p; \ k = 1, \ 2 \dots r, \end{aligned}$$

where  $Y_{ij(1)}$  denotes the observation of the jth individual of  $F_2$  in the ith block;  $Y_{ij''(2)}$ , the observation of the j'th individual of  $F_3$  in the ith block;  $Y_{ij''k(3)}$ , the observation of the kth individual of the j"th augmented line in the ith block;  $f_{2j}$ ,  $f_{3j'}$  and  $c_{j''}$  denote, respectively, the genetic values of the jth  $F_2$  individual, the j'th  $F_3$  individual and the j"th augmented line;  $\mu$  is the unknown population mean and  $b_i$ , the effect of the ith block, i=1, 2...b. Notice that

 $Y_{ij(1)}$  and  $Y_{ij'(2)}$  may or may not exist depending on whether or not the *j*th  $F_2$  and the *j*th  $F_3$  individuals appear in the *i*th block.

Notice further that, since the estimates given in section two are derived under the restriction  $\sum_{j}^{b} f_{2j} + \sum_{j'}^{b} f_{3j'} + br \sum_{j''=1}^{p} c_{j''} = 0$ , the estimates of the genetic values in these examples are actually the estimates of the deviates of the true genetic values from  $\bar{f} = \frac{1}{b(N_{F_2} + N_{F_3} + rp)} \begin{pmatrix} bN_{F_2} \\ \sum_{j'}^{b} f_{2j} + \sum_{j'}^{b} f_{3j'} + br \sum_{j''=1}^{p} c_{j''} \end{pmatrix}$ .

- (b) The random variable e were taken at random from "A Million Random Digits with 10,000 Normal Deviates" of the Rand corporation, published by the Free Press publishers, Glencoe, Illinois, USA. It follows that  $e \sim \text{MID}(0, 1)$ , as in examples 2 and 3. In example 1 we multiply each "e" by 3 to yield  $e \sim \text{MID}(0, 9)$ . In this paper we do not intend to reproduce the observed values of these e's because there are altogether 1200 e's in each example, which would take up a big space for printing.
- (c) The parameters  $f_{2j}$  and  $f_{3j'}$ , j=1,  $2...bN_{F_2}$ , j'=1,  $2...bN_{F_3}$ , were obtained on the supposition of two independent loci, denoted by A-a and B-b, of equal effects and each with two alleles. Hence, given that the additive effects A of -a and B-b be denoted by  $d_a$  and  $d_b$  respectively while the dominant effects of A-a and B-b by  $h_a$  and  $h_b$  respectively, we obtain the genetic values (f's) of the various genotypes as given in Table (3. 2).

**Table 3. 2.** The genetic values  $(f_{2j}$  and  $f_{3j}$ 's) of various genotypes in the  $F_2$  and  $F_3$  individuals

$\begin{array}{c} \text{AABB} \\ d_a + d_b \end{array}$	$AABb \\ d_a + h_b$	$egin{aligned} { m AA}bb \ d_a - d_b \end{aligned}$
$AaBB \\ h_a + d_b$	$AaBb$ $h_a + h_b$	$Aabb \\ h_a - d_b$
$aa  ext{BB} - d_a + d_b$	$aa\mathrm{B}b \ -d_a\!+\!h_b$	$\begin{vmatrix} aabb \\ -d_a - d_b \end{vmatrix}$

(d) Since our interests are centered on the comparison of the senior author's method with that of Mather as regards the estimation of D and H, we purposely allocate the numbers of the  $F_2$  individuals, the  $F_3$  lines and the  $F_3$  individuals in each line to the various genetypes in accordance with the segregation rule as given in tables 3. 3 and 3. 4. Under such an allocation of the number of the  $F_2$  and the  $F_3$  individuals, it is clear that the disturbing effect of the sampling error due to segregation is completely eliminated. In table 3.3 the upper figure denotes the  $F_2$  genotype while the lower figure, the number of  $F_2$  individuals with the indicated genotype in each block.

**Table 3. 3.** The allocation of the number of  $F_2$  individuals to various genotypes in each block

		D0	
	AABB	AABb	AAbb
	2	4	2
$\nabla -a$	A <i>a</i> BB	AaBb	Aabb
V — &	4	8	4
	aaBB	aaBb	aabb
	2	4	2

**Table 3. 4.** The allocation of the  $F_3$  individuals to various genotypes in the  $F_3$  lines

Genotype of F <sub>2</sub> parent	Genotypes and their frequencies of F <sub>8</sub> individuals in F <sub>8</sub> lines
$\left. \begin{array}{c} AABB \\ AAbb \\ aaBB \\ aabb \end{array} \right\} \text{ each with 2 } F_3 \text{ lines}$	AABB 16 AAbb 16 aaBB 16 aabb 16
$   \left. \begin{array}{l}     AaBB \\     Aabb \\     AABb \\     aaBb   \end{array} \right\} each with 4 F3 lines $	AABB 4, AaBB 8, aaBB 4 AAbb 4, Aabb 8, aabb 4 AABB 4, AABb 8, AAbb 4 aaBB 4, aaBb 8, aabb 4
AaBa with 8 F <sub>8</sub> lines	AABB 1, AaBB 2, aaBB 1 AABb 2, AaBb 4, aaBb 2 AAbb 1, Aabb 2, aabb 1

Using the generated data we now proceed to obtain the estimates  $\hat{D}$  and  $\hat{H}$  of D and H by employing the Mather's method as well as the senior author's method. For this purpose we give the relevant quantities in Table 3. 5.

In the Mather's approach, the estimates  $\hat{D}$  and  $\hat{H}$  are obtained by solving the following set of equations using the ordinary least square method

$$\begin{cases} \frac{1}{2}D + \frac{1}{4}H + E_1 = V_{F_2} \\ \frac{1}{2}D + \frac{1}{16}H + E_2 = V_{F_3} \\ \frac{1}{2}D + \frac{1}{8}H + E_3 = \bar{V}_{F_3} \\ E_1 = V_{E_1} \\ E_2 = V_{E_2} \\ E_2 = V_{F_3} \end{cases}$$

**Table 3. 5.** Mather's statistics based on (1) the original observations and (2) the estimated genetic values of the  $F_2$  and the  $F_3$  individuals

		Ex. I	Ex. II	Ex. III
	$V_{F_2}$	16.788	54.528	23.209
Mather's statistics	$V_{\overline{r}_3}$	8.407	44.949	21.588
based on the	$ar{V}_{F_3}$	9.266	16.602	1.210
original	$V_{E_1}$	17.877	21.897	21.747
observations	$V_{E_2}$	9.436	22.291	22.062
	$V_{E_3}$	9.555	0.960	1.040
Mather's statistics	$V_{F_2(c)}$	9.700	32.344	1.446
based on the estimated genetic	$V_{\overline{F}_3(c)}$	0.708	27.132	0.314
values of the $F_2$ and the $F_3$	$\bar{\mathbf{V}}_{\mathbf{F_3}(c)}$	9.184	16.641	1.212
individuals	$\int_{\hat{\sigma}^2}$	9.846	1.301	1.038

 $<sup>\</sup>hat{\sigma}^2$  is obtained from the usual analysis of variance table.

If we write the above as  $X\theta = Z$ , where

$$X = \begin{pmatrix} \frac{1}{2} & \frac{1}{4} & 1 & 0 & 0 \\ \frac{1}{2} & \frac{1}{16} & 0 & 1 & 0 \\ \frac{1}{4} & \frac{1}{8} & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}, \quad \underline{\theta} = \begin{pmatrix} D \\ H \\ E_1 \\ E_2 \\ E_3 \end{pmatrix} \text{ and } \underline{Z} = \begin{pmatrix} V_{F_2} \\ V_{\overline{F}_3} \\ \tilde{V}_{F_3} \\ V_{E_1} \\ V_{E_2} \\ V_{E_3} \end{pmatrix}, \text{ then the estimates } \widehat{D}$$

and  $\hat{H}$  in the Mather's approach are given by

$$\begin{pmatrix} \hat{D} \\ \hat{H} \\ \hat{E}_{1} \\ \hat{E}_{2} \\ \hat{E}_{3} \end{pmatrix} = (X'X)^{-1}X' \begin{pmatrix} V_{F_{2}} \\ V_{F_{3}} \\ V_{F_{3}} \\ V_{E_{1}} \\ V_{E_{2}} \\ V_{E_{2}} \end{pmatrix}.$$

Hence, on substituting the corresponding values from table 3. 6 for the three examples, we obtain

		The second se	
	Ex. 1	Ex. 2	Ex. 3
<b>D</b>	-9.8374	29.386	-15.8642
Ĥ	1.9143	50.434	17.4883
$\mathbf{\hat{E}_{i}}$	21.2326	27.099	26.8483
$\mathbf{\hat{E}_{2}}$	13.2005	27.089	27.6200
$\mathbf{\hat{E}_{3}}$	11.4643	3.1754	3,2085

In the senior author's approach the estimates  $\hat{D}$  and  $\hat{H}$  are obtained by solving the following set of equations using the ordinary least square method.

$$\begin{cases} \frac{1}{2}D + \frac{1}{4}H + K_{1}\sigma^{2} = V_{F_{2}(c)} \\ \frac{1}{2}D + \frac{1}{16}H + K_{2}\sigma_{2} = V_{F_{3}(c)} \\ \frac{1}{4}D + \frac{1}{8}H + \sigma^{2} = \bar{V}_{F_{3}(c)} \\ \sigma^{2} = \hat{\sigma}^{2} \end{cases}$$

where

$$K_1=1+\frac{N_{F_2}}{rp(bN_{F_2}-1)}(b-1)$$
 and  $K_2=\frac{p(a_1b-1)+a_1(b-1)}{rp(ba_1-1)}$ 

Hence, if we denote it by

$$\begin{split} X_1 = & \begin{pmatrix} \frac{1}{2} & \frac{1}{4} & K_1 \\ \frac{1}{2} & \frac{1}{16} & K_2 \\ \frac{1}{4} & \frac{1}{8} & 1 \\ 0 & 0 & 1 \end{pmatrix}, \ \theta_1 = \begin{pmatrix} D \\ H \\ \sigma^2 \end{pmatrix}, \ \underline{Z}_1 = \begin{pmatrix} V_{F_2(e)} \\ V_{\overline{F}_3(e)} \\ \bar{V}_{F_3(e)} \\ \hat{\sigma}^2 \end{pmatrix} \end{split}$$

we obtain the estimates of D, H and  $\sigma^2$  as  $\begin{pmatrix} \hat{D} \\ \hat{H} \\ \hat{\sigma}^2 \end{pmatrix} = (X_1'X_1)^{-1}X_1'Z_1$ .

On substituting the relevant values from table 3. 6 for the three examples we obtain

	Ex. 1	Ex. 2	Ex. 3
<b>D</b>	0.107	51.429	0.396
Ĥ	-1.328	21.212	0.717
$\hat{\sigma^2}$	9.673	1.247	1.037

#### Comments

As the main purpose of the senior author's approach is to allow for a better control over the soil hetergeneity of blocks than that of Mathers, it might be expected that the senior author's approach would be more efficient than that of Mather as regards the estimation of D and H. This is in fact evidenced from the results of the three generated examples, as given in the previous section.

From table 3. 6 it seems, however, that the efficiency of the senior author's method depends in turn on the values of  $\sigma^2$ , D and H. This may seem to be

**Table 3. 6.** Comparison of the senior author's method with that of Mather as regards the estimation of D and H

Ex. I

	Theoretical value	Mather's Method	Author's Method
<b>D</b>	0.5	-9.8374	0.107
H	0.18	1.9143	-1.3280
$E_1 = \cdots = E_{n-1}$		21.2326	
$\mathbf{E_2}$		13.2005	
$E_8 (=\sigma^2)$	9.00	11.4643	9.673

Ex. II

	Constant and Const		The state of the s
	Theoretical value	Mather's Method	Author's Method
D	50.00	29.386	51.429
H	18.00	50.434	21.212
$\mathbf{E_i}$		27.099	
$E_2$		27.989	
$E_3 (=\sigma^2)$	1.00	3.1754	1.247

Ex. III

Procedure and the second secon	1	`heoretical value	Mather's Method	Author's Method
D		0.50	-15.9643	0.396
Н		0.18	17.4883	0.717
$\mathbf{E_1}$		*	26.8483	
$\mathbf{E_2}$			27.6200	
$E_3(=\sigma^2)$		1.0	3.2085	1.037

attributable to the adoption of the ordinary least square method. For it is well known that the efficiency of the estimates  $\hat{\theta} = (X'X)^{-1}X'Y$  in  $EY = X\theta$  depends on the supposition of  $V_2 = \sigma^2 I_n$ . Since in both the senior author's approach and the Mather's approach this assumption is obviously not valid, the efficiency of both the senior author's and the Mather's Methods are therefore related to the degree of deviation of the variances of the Mather's statistics from the standart form  $\sigma^2 I_n$ . For large  $\sigma^2$  such an inflation is expected to become appreciable, as evidenced from example 1, of the previous section.

From table 3. 6, while it is true that the senior author's method is less efficient for large  $\sigma^2$  and small D and H (see results of example 1), it might be a useful method for small  $\sigma^2$  and large D and H and large block differences (see results of examples 2 and 3). As noted in section two, the APBIB design

seems to be able to reduce  $\sigma^2$  to some extend, the senior author's method may seem therefore worthy trying, especially when the block differences are big.

## Summary

- (a) In this paper three numerical examples were generated using the relevant parameters given in Table 3.1 and employing a fixed model, together with the rules as specified in section 3. Using these generated data we compute the estimates of the genetic variances D and H in section 3 by employing the Mather's as well as the senior author's method as developed in (2). The results are given in Table 3.6, which indicate that in all cases the senior author's method seems to be superior to that of Mather (1949) as regards the estimation of D and H. Such a result is to be expected since the senior author's approach may seem to allow for a better control over the soil hetererogeneity than that of Mather.
- (b) While it might be true that the senior author's approach might be better then that of Mather for the estimation of genetic variances, it seems that the efficiency of the senior author's approach is also very low in case  $\sigma^2$  is large while D and H are small. This is attributed to the adoption of the ordinary least square method whose efficiency is closely related to the degree of the deviation of the covariance matrix of  $V_{\mathbb{F}_2(e)}$ ,  $V_{\mathbb{F}_3(e)}$ ,  $\bar{V}_{\mathbb{F}_3(e)}$  and  $\hat{\sigma}^2$  from the standard form  $\sigma^2 I_4$ .

# 再論數量遺傳之分析方法

#### 譚 外 元 魏 書 駁

- (1) 本文第一作者會提供另一方法籍以分析數量遺傳之資料。茲爲比較本文第一作者之方法與 Mather 方法起見,筆者等持利用常態逢機數字表及表 (3.1) 之介量數值而構成三個實例如第三節所示。根據此三實例之計導結果顯示本文第一作者之方法一般均較 Mather 方法爲優。
- (2) 根據表 3.6 之結果,可見筆者之方法之效率與  $\sigma^2$ , D 及 H 之大小有關。如  $\sigma^2$  甚大,則筆者之方法亦不如理想。究其原因可能爲由於使用通常之最小二乘方法以解 D 與 H 所以致。

#### References

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